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On the Non-Stationarity of
German Income Mobility
(and Some Observations on
Poverty Dynamics)

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On the non-stationarity of German income mobility (and some observations on poverty dynamics)

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Abstract

The intra-distributional mobility of German income dynamics is analysed using GSOEP. Transition probabilities are found to be time-varying. The tested models comprise various mixed Markov chains in discrete time and a non-stationary mover-stayer model is proposed. In order to explain the observed mobility profiles, we concentrate on one important income class -the poor- instead of the entire transition matrix. Various poverty duration models are examined.

keywords: intra-distributional mobility, Markovian models, time-varying transition probabilities, poverty.

JEL classification: C41, D31, I32

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1 Introduction

The study of income dynamics can be divided into the distinct tasks of examining the shape dynamics of the income distribution, and investigating intra-distributional mobility. Whilst the former enjoys much popularity because cross-sectional data is often readily accessible, the latter task is more elusive, and a common prejudice is that (at least in Germany) mobility is low. The German Socio-Economic Panel (GSOEP) is used in this paper to examine income mobility for the German case. This characterisation is made in two stages. The first stage is descriptive and consists of estimating various Markov models (and a new mover-stayer model is proposed). The second stage goes beyond mere description and attempts to explain the observed mobility.

Some stylised facts about German income dynamics in the period 1983 to 1989 can be established by examining Figures 1 to 3. The shape of the net income distribution has hardly changed in this period ¹. But in contrast to this seeming 'stability', the time series of summary statistics of the transition matrices, such as the Shorrocks (1978) mobility index depicted in Figure 2, reveal that mobility dynamics behave differently. The lack of action at the surface conceals substantial movements beneath it. Several features emerge. The statistic is not a constant, suggesting that the underlying transition probabilities are time-varying. In fact, there is a downwards trend which implies a consistent fall of income mobility over the years except for the last year. Since the Shorrocks mobility index is the inverse of the harmonic mean of expected durations of remaining in a given part of the cross-section distribution, the lower panel of the figure depicts the time series of the staying probabilities. For the three richest income groups, these have a tendency to rise, but not monotonically and some movements are in opposite directions. By contrast, the lowest income group - the poor - experience a dramatic increase in immobility, but there is also a sharp fall in the last year.

Another way of assessing income mobility is to examine the contourplots of the stochastic kernel density estimates, depicted in Figure 3. They are more

¹The changes in the shape of the distribution are minor when compared to the vast changes experienced in the UK (Cowell, Jenkins, and Litchfield (1996)) or the US (Burkhauser, Crews, Daly, and Jenkins (1995)) in the 1980s. In both cases, a dramatic polarisation has taken place; nearly unimodal shapes have turned into twin-peaks as the middle class occupies a sinking valley between them. As Jenkins (1995) observes: "The shift away from the middle class in both directions is strong evidence that the 'middle class' was shrunk, however one defines the middle." Fears of a shrinking German middle class are currently unfounded.

general than transition matrices as they do not impose an arbitrary grouping of information. There is a remarkable stability in the middle income group but important changes happen in the lower and upper income groups. All this evidence suggests that the mobility process is very complicated.

Such changes in the mobility dynamics are clearly important when welfare assessments of income distributions are not static, but attempt to capture income histories. Changing income mobility indicates changing opportunities, and according to some commentators changing fairness². Concentrating exclusively on the shape dynamics of the income distribution - seemingly unchanged in the German case - would ignore one important dimension of welfare.

Several models are tested which might explain the stylised facts. Section 3 and 4 examine pure and mixed Markovian models in discrete time, such as a (new) non-stationary mover-stayer model. The next section attempts to explain the observed mobility. The method pursued here is to concentrate on one important income state instead of the entire transition matrix, and the chosen income state is poverty since this group has experienced the most dramatic changes in mobility. Section 5.1 explains the chances of escaping or descending into poverty by means of a Markov model which accounts both for the non-stationarity of the data and the heterogeneity of the population. A second class of models, analysed in section 5.2, comprises duration models. Section 6 concludes.

²Friedman (1962), for instance, considers "two societies that have the same distribution of annual income. In one there is great mobility and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other, there is great rigidity so that each family stays in the same position year after year. Clearly, in any meaningful sense, the second would be the more unequal society" (p.171).

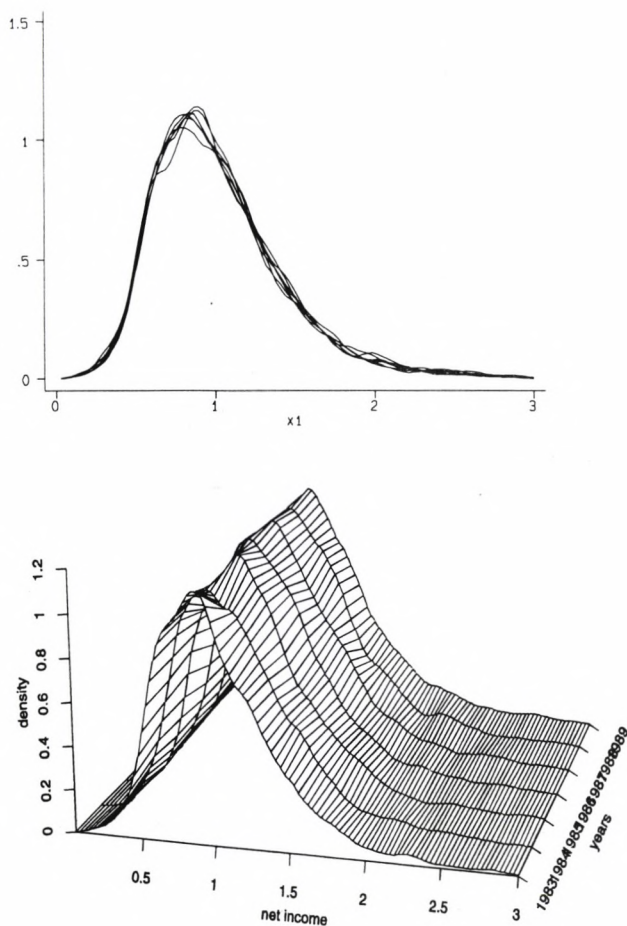


Figure 1: Shape dynamics of the net income distribution. Net income is normalised at the contemporaneous mean. The kernel density estimator uses the Epanechnikov kernel and the bandwidth is chosen using cross-validation methods.

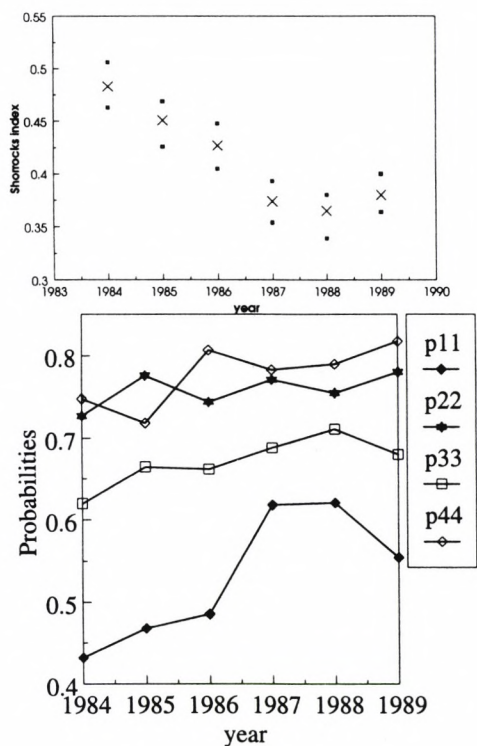


Figure 2: Upper Panel: Time series of the Shorrocks mobility index, bracketed by estimated 10% confidence intervals. Lower Panel: Time series of staying probabilities.

Notes: If $P = [p_{ij}]$ denotes the $n \times n$ transition matrix, the Shorrocks index proposed in (Shorrocks 1978) is defined as $\mu(P) = (n - \text{tr}(P))/(n - 1)$. It is the inverse of the harmonic mean of expected durations of remaining in a given part of the cross section distribution. The higher the index, the lower is the persistence or the greater is the mobility. The transition probabilities are estimated using their maximum likelihood estimator (cf. section 3). The confidence intervals were computed using bootstrapping and (Efron 1987)'s BC_α method. The transition matrices were defined on the weighted data.

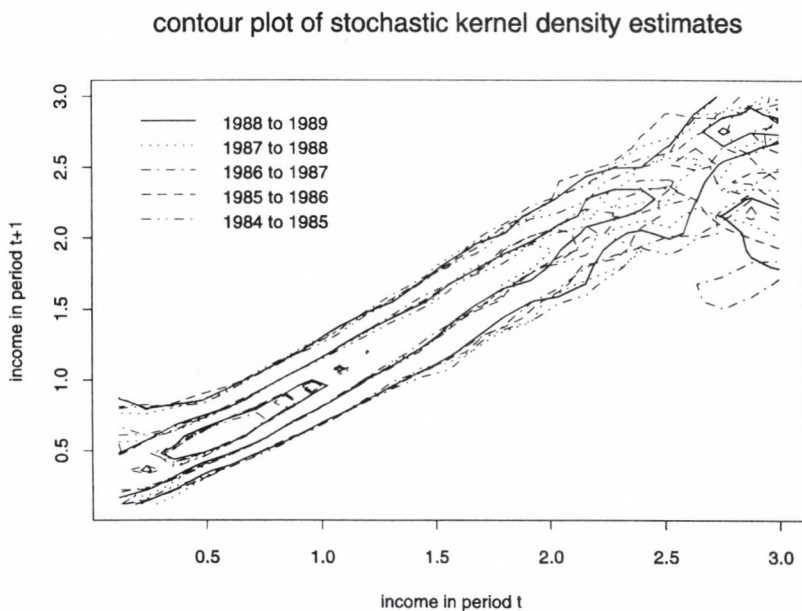


Figure 3: contour plots of the stochastic kernel density estimates 1984-1985 to 1988-1989. Income is normalised at the contemporaneous median.

2 The Data

In this paper the German panel dataset GSOEP is used in its incarnation as the "Equivalent Datafile". Comprising the years 1984 to 1990, the latter is a subset of the former and not only contains its principal income variable but also includes some derived variables, the most important being post-tax post-benefit income. Since GSOEP proper was described in detail in Schluter (1996), a brief outline should suffice. Two income concepts are used. The elements of annual gross (pre-tax pre-benefit) income are raw data but need to be aggregated. However, the Equivalent Datafile conveniently supplies an estimate of annual household post-tax post-benefit income, which is derived from the gross income data by means of a tax-benefit simulation. This income variable is computed as the sum of total family income from earnings, asset flows, private and public transfers, the imputed rental value of owner occupied housing, and a tax simulation is applied.

In order to take account of scale economies within the household, income was equivalised using the OECD equivalent scales. Disposable income was divided by household size raised to the power 0.5. This choice of equivalence scales had been made for two reasons. First, Burkhauser, Merz, and Smeeding (1994) show that the German Social Assistance scale implies scale economies which are too low. Second, the use of the OECD scale, being the standard scale for datasets included in the LIS project, facilitates first ad hoc international comparisons.

Finally, incomes were standardised at 1991 prices. The data remained unweighted for the subsequent estimation procedures. The sample examined in this paper was selected by keeping only persons with a complete income record for the years 1984 to 1990. This selection procedure resulted in 9022 observations. Subsequently, the income data is analysed by means of transition matrices. Four income groups were defined with respect to the contemporaneous median (a statistic which is robust against outliers). The poverty line is set (arbitrarily) at 0.5 times median income. Modest incomes are equivalised incomes between 0.5 and 1 times the median. Middle incomes are between 1 and 1.5 times the median. Finally, high incomes are those above 1.5 times the median. The choice of these income groups is inherently arbitrary, but the relative definition of poverty applied in this paper has become standard practise for European countries.

3 Pure Markov models in discrete time

This section explores the extent to which standard Markovian models can explain the observed income transitions. Competing models are juxtaposed, and the following sequence of tests is conducted: non-stationary and stationary Markov chains of the same order are tested against each other. Then, a non-stationary first order chain is tested against a non-stationary second order chain. These tests were first developed by Anderson and Goodman (1957).

3.1 First order Markov chains

Let $P(t) = [p_{ij}(t)]$ be an $m \times m$ transition matrix where $p_{ij}(t)$ denotes the conditional probability of moving to state j in the current period, given that state i was occupied in the preceding period. The chain is observed up to time T at time points $t = 1, 2, \dots, T$. If the chain is stationary $p_{ij}(t_1) = p_{ij}(t_2) = p_{ij}$, $\forall t_1, t_2$. Let $N(t) = [n_{ij}(t)]$ denote the associated matrix of actual transition counts. The transition probabilities $p_{ij}(t)$ need to be estimated. Since these are multinomially distributed, their maximum likelihood estimator $\hat{p}_{ij}(t)$ can be derived by maximising the likelihood function, conditional on the initial distribution

$$\log L = \sum_t \sum_i \sum_j n_{ij}(t) \cdot \log p_{ij}(t)$$

subject to $P(t)$ being a stochastic matrix. The Lagrangean for this programme is

$$\mathcal{L} = \sum_t \sum_i \sum_j n_{ij}(t) \log p_{ij}(t) - \sum_t \sum_i \lambda_{ti} \left(\sum_j p_{ij}(t) - 1 \right)$$

The first order condition implies $n_{ij}(t) = \lambda_{ti} \cdot \hat{p}_{ij}(t)$. Summing out j yields $\lambda_{ti} = \sum_j n_{ij}(t)$, which upon substitution gives the estimator

$$\hat{p}_{ij}(t) = \frac{n_{ij}(t)}{\sum_j n_{ij}(t)}$$

being a simple frequency count. For the stationary model, a similar calculation gives the maximum likelihood estimator ³

$$\tilde{p}_{ij} = \frac{\sum_{t=1}^T n_{ij}(t)}{\sum_{t=1}^T \sum_j n_{ij}(t)} = \frac{\sum_{t=1}^T n_{ij}(t)}{\sum_{t=1}^T n_{i+}(t)}$$

where $\sum_j n_{ij}(t) = n_{i+}(t)$ for notational convenience.

Given these functions, tests for non-stationarity can be easily implemented. Let the null hypothesis be that the transition probabilities are stationary, i.e. $\mathcal{H}_0: p_{ij}(t) = p_{ij} \quad \forall t, i, j$. Using the respective likelihood functions, the likelihood ratio is

$$\log \lambda = \sum_t \sum_i \sum_j n_{ij}(t) \cdot \{\log \tilde{p}_{ij} - \log \hat{p}_{ij}(t)\}$$

and $-2 \log \lambda$ is asymptotically distributed as χ^2 with $(T-1)m(m-1)$ degrees of freedom⁴. If the null hypothesis is true, an asymptotically equivalent test is based on the similarity between transition matrices and contingency tables. The well-known χ^2 -test then gives the test statistic

$$X^2 = \sum_i X_i^2 = \sum_i \sum_t \sum_j n_{i+} \cdot \frac{\tilde{p}_{ij} - \hat{p}_{ij}(t)}{\tilde{p}_{ij}}$$

which is asymptotically distributed as χ^2 with $m(m-1)(T-1)$ degrees of freedom. However, Anderson and Goodman (1957) show that if the null hypothesis is not true, the power of the χ^2 -test can be different from the power of the likelihood test. Thus both tests should be performed.

Since a direct inspection of the transition matrices or the time series of the mobility index suggests non-stationarity, it is not surprising that both tests confirm the greater explanatory power of the non-stationary model. The test statistics evaluate to $-2 \log \lambda = 336.3$ and $X^2 = 341.4$.

3.2 Second order Markov chains

The methods of the preceding paragraphs extend in a very natural manner to second order Markov chains. $P(t) = [p_{ijk}(t)]$ denotes the conditional probability of being in state k at time t , given states i and j at times $t-2$ and $t-1$

³Anderson and Goodman (1957) show its asymptotic sampling distribution to be normal.

⁴See Rao (1973). The number of degrees of freedom of the asymptotic χ^2 -distribution equals the number of linearly independent restrictions. Note that P is a stochastic matrix.

respectively. Again, the transition probabilities are estimated by maximising the log-likelihood function, and similar likelihood ratio and χ^2 - tests apply.

The tests suggest once again that the non-stationary (second order) model has a greater explanatory power than the stationary model. The test statistics evaluate to $-2 \log \lambda = 561.4$ and $\chi^2 = 545.7$.

3.3 First order against second order Markov chains

The theoretical results of the two preceding sections can be combined in order to test which order of the non-stationary model has the greater explanatory power. If the null hypothesis is that a first order non-stationary model is applicable, $p_{1jk} = p_{2jk} = \dots = p_{mjk} = p_{jk}, \forall j, k$, the likelihood ratio becomes

$$\log \lambda = \sum_t \sum_i \sum_j \sum_k n_{ijk}(t) \cdot \{\log \hat{p}_{jk} - \log \hat{p}_{ijk}\}$$

$-2 \log \lambda$ being asymptotically distributed as χ^2 with Tm^2 degrees of freedom.

Performing this test, the statistic evaluates to $-2 \log \lambda = 2,955.8$, being very significant evidence against the null hypothesis. In consequence, the memory of the process governing income transitions extends over more than one period.

4 Mixed Markovian models in discrete time

Pure Markovian models are popular both in the theoretical as well as in the empirical literature because of their mathematical structure. Yet, as the previous section demonstrated, they do not fit the data too well. One principal assumption underlying their estimation is the 'homogeneity of persons': individuals are the same except for their income. This assumption is likely to be flawed. Indeed, results derived elsewhere suggest that the population is very heterogeneous. Schluter (1996), for instance, depicts for several socio-economic groups income distributions which differ dramatically. In contrast to this observable heterogeneity, some latent variable may be important. A particular type of unobservable heterogeneity is treated next.

The next level of complexity is achieved by mixing independent Markovian models, the easiest of which is the following mover-stayer model. An unobservable fraction of the population stays with certainty in its income group for all periods, whilst the evolution of incomes of everyone else, the movers, is determined by a non-degenerate first order Markov chain. The pure Markovian model is nested within this richer structure, since stayers may not be present. This nesting gives rise to a natural test, a likelihood ratio test, by means of which to discriminate between these two models.

4.1 A mover-stayer model : the stationary case

Although Goodman (1961) presents an extensive mathematical treatment of this model, his estimators, proposed without derivation, fail to be maximum likelihood estimators. These are supplied in Frydman (1984) where transitions are stationary.⁵ A non-stationary model is proposed below.

Let the unobserved fraction of the population who are stayers in income group i be denoted by s_i . The income of movers $(1 - s_i)$ evolves according to the stationary first order Markov chain with $m \times m$ transition matrix $M = [m_{ij}]$. The composite process thus evolves according to $P(t) = SI + (I - S)M^t$ where S is a diagonal matrix with entries s_i . Let $n_i(t)$ denote the number of persons in state i at time t , n_i the number of persons staying in state i during the entire period of observation, $n_{ik} = \sum_t n_{ik}(t)$ the total number of transitions from state i to state k , $n_i^* = \sum_t n_i(t - 1)$, and n the total number of persons. The log-likelihood function conditional on the initial distribution can be factorised thus

$$\begin{aligned} \log L(s, M) = & \sum_i n_i \log [s_i + (1 - s_i)m_{ii}^T] \\ & + \sum_i [n_i(0) - n_i] \log (1 - s_i) + [n_{ii} - Tn_i] \log m_{ii} \\ & + \sum_i \sum_{k \neq i} n_{ik} \log m_{ik} \end{aligned} \quad (1)$$

The last summation pertains only to transition between unequal states, and thus concerns only movers. As regards the first sum, a person may remain in

⁵McCall (1971) applies the mover-stayer model to the issue of earnings mobility. He simplifies the estimator proposed in Goodman (1961) by letting $T \rightarrow \infty$ despite the fact that his empirical time series is very short.

income class i for two reasons: either he is a stayer with probability s_i , or with probability $(1 - s_i)$ he is a mover but remains in that state for T consecutive periods with probability m_{ii}^T . The second term captures movers returning to their initial state, who have at least once left it.

The maximisation strategy is to resubstitute solutions from the first order conditions into the objective function⁶. Eventually the size of the equations system is reduced to the number of income classes, and the equations for \hat{m}_{ii} can be solved numerically. The estimators of the off-diagonal elements \hat{m}_{ij} are then computed recursively

$$\hat{m}_{ij} = n_{ij}(1 - \hat{m}_{ii} - \sum_{\substack{k=1 \\ k \neq i}}^{j-1} \hat{m}_{ik}) / \sum_{\substack{k=j \\ k \neq i}} n_{ik}$$

The estimates for the stayers are⁷

$$\hat{s}_i = \frac{n_i - n_i(0) \hat{m}_{ii}^T}{n_i(0)(1 - \hat{m}_{ii}^T)} = 1 - \frac{n_i(0) - n_i}{n_i(0)(1 - \hat{m}_{ii}^T)} \quad (2)$$

the last term being the ratio of the observed to the expected number of persons who make a least one transition from state i during T periods.

Since the pure Markovian model is nested within the mover-stayer model, their relative performance can be assessed using a likelihood ratio test. Let the null hypothesis be that the pure model is appropriate ($s_i = 0, \forall i$). The maximised likelihood of the pure model is $\log(L_{s=0}) = \sum_i n_i(0) \log(n_i(0) - n) + \sum_{i,k} n_{ik} \log(n_{ik}/n_i^*)$. Denote the ratio of the likelihoods by λ , $-2 \log \lambda$ is distributed as χ^2 with m degrees of freedom.⁸ Can the statistical significance of an individual s_i be tested? If T and \hat{m}_{ii} are such that \hat{m}_{ii}^T is negligible, the estimator for s_i simplifies to $\hat{s}_i = n_i/n_i(0)$, being the fraction of persons initially in state i who remain there for all consecutive periods. In this case Goodman (1961)'s argument applies. Let \tilde{p}_{ij} denote the estimator of the stationary first

⁶Amemiya (1985) proposes an alternative method of estimation. Two equation systems are established by considering transitions within two periods, viz. $P = SI + (I - S)M$ and $P^{(2)} = SI + (I - S)M^2$. P and $P^{(2)}$ can be consistently estimated by the maximum likelihood estimators presented in the preceding sections. Resubstituting these yields $2m(m-1)$ equations in m^2 unknowns. However, Frydman's estimation strategy is more parsimonious.

⁷This estimator may become useless if the observation period T is small, since \hat{s}_i may become negative as Frydman failed to impose a non-negativity constraint. This problem decays with m_{ii}^T as T increases.

⁸See Rao (1973). The number of degrees of freedom of the asymptotic χ^2 -distribution equals the number of linearly independent restrictions. There are m restrictions imposed, viz. $\{s_i = 0\}_{i=1}^m$.

order Markov chain derived in the previous section. The test is based on a comparison between \hat{s} and its expected value \tilde{p}_{ii}^T . $(\hat{s} - \tilde{p}_{ii}^T)$ is normally distributed with mean zero and a variance which can be consistently estimated by $\hat{\sigma}^2 = \tilde{p}_{ii}^T(1 - \tilde{p}_{ii}^T)/n_i(0) - n\tilde{p}_{ii}^{2T-1}(1 - \tilde{p}_{ii}^T)/\bar{n}_i$, where $\bar{n}_i = \sum_t n_i(t)/T$. Under the null hypothesis $s_i = 0$, and $X_i^2 = (\hat{s} - \tilde{p}_{ii}^T)/\hat{\sigma}^2$ is distributed as χ^2 with one degree of freedom.

The estimated transitions matrix is not reported here for the sake of brevity. Compared to the pure model, probability mass has been redistributed away from the main diagonal. The movers are thus more mobile than the pure model suggests. The stayers fractions are estimated to be $\hat{s} = (0.1; 0.224; 0.04; 0.14)$. Testing the competing models, the likelihood ratio test confirms the greater explanatory power of the mover-stayer model ($-2 \log \lambda = 23,147.8$). These estimates have a profound implication, since the first income group is occupied by the poor (whose income falls short of the contemporaneous poverty line). Income mobility is sufficiently high so that most persons are able to escape poverty at least temporarily. Yet, a statistically significant 10%⁹ of those deemed into poverty at the beginning of the observation period constitute a hard-core of poverty¹⁰ - remaining poor with certainty.

These results, of course, have to be taken with a pinch of salt, as the previous section suggested that income transitions are non-stationary. The problem caused by time-varying transition probabilities is addressed in the next section.

4.2 A mover-stayer model: the non-stationary case

The previous model can be generalised so that non-stationarity in income transitions can be admitted. Let movers transit according to the non-stationary first order Markov chain $M(t)$. In consequence, the composite process evolves according to $P(t) = SI + (I - S) \prod_{\tau=1}^t M(\tau)$. Analogous to equation (1), the likelihood function can be written as

$$\log L(s, M(1), \dots, M(T)) = \sum_i n_i \log \left(s_i + (1 - s_i) \prod_{\tau} m_{ii}(\tau) \right) \quad (3)$$

⁹Applying the above test to the estimate of s_1 , the estimate of the hard-core of poverty, yields a statistically significant result ($\chi_1^2 = 3,766.8$).

¹⁰Labelled by McCall (1971) the "back-wash hypothesis".

$$\begin{aligned}
& + \sum_i (n_i(0) - n_i) \log(1 - s_i) \\
& + \sum_i \sum_\tau (n_{ii}(\tau) - n_i) \log m_{ii}(\tau) \\
& + \sum_i \sum_\tau \sum_{k \neq i} n_{ik}(\tau) \log m_{ik}(\tau)
\end{aligned}$$

Observe that the stationary case of equation (1) is nested within equation (3). Maximising this with respect to s_i yields the estimator

$$s_i = \frac{n_i - n_i(0) \prod_\tau m_{ii}(\tau)}{n_i(0) (1 - \prod_\tau m_{ii}(\tau))} \quad (4)$$

(compare to (2).) Resubstituting this into equation (3) yields

$$\begin{aligned}
\log L(\hat{s}, M(1), \dots, M(T)) &= c - \sum_i (n_i(0) - n_i) \log \left(1 - \prod_\tau m_{ii}(\tau) \right) \\
&+ \sum_i \sum_\tau (n_{ii}(\tau) - n_i) \log m_{ii}(\tau) \\
&+ \sum_i \sum_\tau \sum_{k \neq i} n_{ik}(\tau) \log m_{ik}(\tau)
\end{aligned}$$

where c denotes a constant. The Lagrangean of this problem is

$$\mathcal{L} = \log L(\hat{s}, M(1), \dots, M(T)) - \sum_i \sum_\tau \lambda_i(t) \left(\sum_k m_{ik}(t) - 1 \right)$$

Maximising this with respect to $m_{ii}(t)$ and $m_{ik}(t)$, summing these and solving out the Lagrange multipliers $\lambda_i(t)$ yields a non-linear equations system for $m_{ii}(t)$

$$n_{ii}(t) - n_i = (n_{i+}(t) - n_i) m_{ii}(t) + \left[n_i(0) - n_i \frac{\prod_\tau m_{ii}(\tau)}{1 - \prod_\tau m_{ii}(\tau)} \right] m_{ii}(t)$$

This is a non-linear system comprising T equations in T unknowns with solution $\hat{m}_{ii} = (\hat{m}_{ii}(1), \dots, \hat{m}_{ii}(T)) \in [0, 1]^T$. It is solved numerically using the multidimensional Newton's method (see Press, Teukolsky, Vetterling, and Flannery (1992)). The solutions to $\hat{m}_{ik}(t)$ and \hat{s}_i are then computed recursively.

Tests of hypotheses can be implemented following the methods outlined in the previous sections.

This estimation procedure resulted in the following estimates for the stayers $\hat{s} = (0.11; 0.33; 0.13; 0.31)$. Compared to the stationary model, the estimates

of the fraction of the poor has not changed, whilst the other estimates all have increased. As regards the mover probabilities, the entries of $M(t)$ follow the changes suggested by the movement of the Shorrocks mobility index. Probability mass is moved onto the main diagonal as time passes, suggesting that incomes have become more immobile.

5 Poverty re-examined

The aim of this section is to go beyond the descriptive Markov models of the preceding sections and to attempt to explain the observed mobility profiles. Instead of analysing the entire transition matrix, we concentrate on one important income state - poverty - and analyse the processes governing the movements into and out of poverty. Two types of models are examined.

5.1 A Markov model with observed heterogeneity

This section examines a two state Markov model with exogenous variables as proposed in Boskin and Nold (1975) and further discussed in Amemiya (1985). Person i may be in either of two states: either he is in poverty at time t , $y_i(t) = 1$, or he is not $y_i(t) = 0$. The probability of being in poverty conditional on the preceding state is $\Pr(y_i(t) = 1 | y_i(t-1)) = F(\beta'x_i(t) + \gamma'x_i(t)y_i(t-1))$ where $F(\cdot)$ is a distribution function with corresponding density f . Thus, the model is a generalised first order Markov model, in which the exogenous variables $x_i(t)$ exhibit non-stationarity and heterogeneity amongst persons. This formulation nests within it a variety of observationally equivalent models, depending on the parametrisation of γ . For instance, setting $\gamma = -(\alpha + \beta)$ and if f is symmetric, the model has the following interpretation. The (conditional) probability of person i entering poverty is determined as $p_{01}^i(t) = F(\beta'x_i(t))$, whereas the (conditional) probability of escaping poverty is $p_{10}^i(t) = F(\alpha'x_i(t))$. Thus the profile of a representative person entering poverty is stipulated to be different from that of a representative person escaping poverty.

The log-likelihood function can be written as

$$\begin{aligned} \log L(\alpha, \beta) = & \sum_i \sum_t y_i(t) \log F(\beta'x_i(t) + \gamma'x_i(t)y_i(t-1)) \\ & + (1 - y_i(t)) \log [1 - F(\beta'x_i(t) + \gamma'x_i(t)y_i(t-1))] \end{aligned}$$

The distribution function is chosen to be logistic $F(x) = e^x / (1 + e^x)$, so that the objective function is globally concave and the estimation step reduces to estimating a standard logit model. The maximisation strategy is to employ the iterative method of scoring separately for each parameter. The MLE is consistent and asymptotically normal (see Amemiya (1985)). Note also that the indices $(i; t)$ can be treated as a single index. Thus, although the time series is relatively short but the cross section is large, the sample can be considered to be large.

The sample was chosen to contain only persons above the age of 20 in order to focus on the causes of poverty, a step which reduces the size of the sample to 6266 observations. The regressors comprise: indicators for employment status, disability, and household size in a given year ¹¹, nationality, the age, and education level (measured in years) of the person in the year 1984. The importance of these variables is not surprising given the results of a static analysis in Schluter (1996) who estimates the income distributions for various partitions of the sample using kernel density estimators.

¹¹Bane and Ellwood (1985), for instance, emphasise the importance of the household formation process as a determinant of poverty in the case of the US.

Both weighted and unweighted data are used and Table 1 collects the estimation results. The results contain some surprises. As regards the unweighted data, the probability of escaping poverty is higher when a person is a German, is well educated, healthy and ends unemployment spells quickly. This last ability is the most decisive and the relative size of the parameter estimate is perhaps astonishing. More formally, the relative importance of the variables can be assessed by computing an elasticity such as $\eta_{i,j} := (\partial p_{01}^i(t) / \partial x_j^i(t)) / (x_j^i(t) / p_{01}^i(t)) = \beta_j(1 - p_{01}^i(t))x_j^i(t)$ which approximates the effect of a change in a discrete variable x_j for person i . The effect of becoming unemployed is dramatic: $\eta_{i,unemployed} = 1.53(1 - p_{01}^i(t))$ (but this effect diminishes as $\beta'x^i(t)$ increases). Unemployment and nationality are of even greater importance for those escaping poverty.

The coefficient for nationality is large but this may be due to oversampling foreigners. When the data is weighted, the coefficient on nationality is expected to fall because foreigners were oversampled. Surprisingly, the coefficient is only slightly lower, but the employment status coefficient is markedly higher. This implies a different profile for persons slipping into poverty. For Germans, the principal reason appears to be unemployment, whilst it seems to be low earnings for foreigners.

5.2 Semi-Markov processes: non-stationary duration models

The discrete time models of the preceding sections have to confronted the time aggregation problem, highlighted in Singer and Spilerman (1976), caused by the absence of a natural time unit: income transitions do not happen at the end of regularly spaced intervals which coincide with those of the panel survey. As a consequence, parameter estimates cannot be interpreted as structural information. In this case it is more appropriate to fit a continuous time model. But this strategy gives rise to two problems. First, the model needs to be formulated in such a way that the actual discrete time observation is embeddable within the continuous time model. A nice set of necessary and sufficient conditions has yet not been found.¹²

¹²Geweke, Marshall, and Zarkin (1986), for instance, present a calculation to test the embeddability of a discrete first order stationary Markov chain within a stationary continuous time model. See also their references for the embeddability problem.

The second problem is caused by the particular data under scrutiny, viz. their non-stationarity. Whilst it is impracticable to estimate a general continuous time Markov chain, researchers have pursued two avenues. Singer and Spilerman (1976) discuss (but do not estimate) a mixture model in which transitions follow a stationary Markov chain but waiting times between transitions may vary with time. A second possibility and the strategy pursued below is to focus on one economically meaningful state, such as poverty, and to estimate a parametrised duration model.

This section presents a standard duration model as outlined in Cox and Oakes (1984) and follows suggestions of Amemiya (1985). Person i may be in either of two states: either he is poor or he is not. The time in poverty T , i.e. the length of the poverty spell, is a random variable with distribution F and associated density f . If the population is heterogeneous, these may differ across persons, written as F_i . It is convenient to work with the hazard rate $\lambda_i(t) := f_i(t) / [1 - F_i(t)]$ where $\lambda_i(t) \Delta t$ has a probabilistic interpretation: it is the probability that, given the person has not left poverty in the time interval $(0, t)$, he will do so the next moment, i.e. in $(t, t + \Delta t)$. A basic assumption of the continuous time model is reminiscent of Poisson processes, since the probability that a person changes her income state more than once in a small time interval $(t, t + \Delta t)$ is negligible. $\lambda_i(t)$ may vary with time. The duration function F can then be written as

$$F_i(t) = 1 - \exp\left\{-\int_0^t \lambda_i(z) dz\right\} \quad (5)$$

If person i completes J poverty spells of individual length $t_{i,j}$ the contribution to the likelihood function is $\prod_{j=1}^J f_i(t_{i,j})$. However, the estimation problem is complicated by the fact that person i may have censored spells. A spell at the end of the panel t^* is right-censored and thus incomplete if the person cannot be observed to leave that state, leading to the contribution $1 - F_i(t^*)$ to the likelihood function. A spell is left-censored if person i is in poverty at the beginning of the panel, and may have been in this state for a long time. Amemiya (1985) shows that the contribution to the likelihood function then is $[1 - F_i(t)] / \int s f_i(s) ds$.¹³ For the sample under scrutiny Table 2 collects in-

¹³In some applications, such as duration models of criminal recidivism or fertility, the probability of eventual "failure" is less than one; some censored observations will never "fail". If the survival function is thus defective for some persons, Schmidt and Witte (1989) propose to use a split population model, which parametrises $\Pr\{\text{never fail}\} = 1 - G(\alpha'z_i) = 1 - 1/(1 + \exp(\alpha'z_i))$, where z_i is a vector of explanatory variables. The likelihood function then needs to be adjusted accordingly.

length [years]	numbers of spells	left censored	right censored
1	893	194	145
2	246	62	63
3	113	19	53
4	64	16	27
5	33	6	23
6	30	10	20
7	51	51	51

Table 2: Poverty spells: incidence, duration, and censoring

formation on the incidence and duration of poverty spells, and the extent of censoring.

The problem, of course, is how to parametrise the hazard rate $\lambda_i(t)$. A parametrisation, popular in the econometrics of labour turnover, is a Cox proportional hazard rate $\lambda_i(t) = h(t) \exp(\beta'x_i(t))$, where $x_i(t)$ is a vector of time-varying exogenous variables. Following the previous Markov model, $x_i(t)$ includes two different processes: an unemployment process and a household formation process which traces the evolution of the size of the household. Note that the parameter β does not vary with the number of spells. The baseline hazard rate $h(t)$ captures duration dependence of the poverty process.

The parameters are estimated by maximising the (partial) likelihood function¹⁴, but in order to simplify the estimation problem left censored spells were deleted. In order to evaluate the integral in (5) with discrete data, the exogenous variables were assumed to remain constant during the interval between observations.

The estimation results on the unweighted data are reported in Table 3.

Both the nationality and the age variable are not significant. An increased household size increases the poverty hazard. But most important, confirming the evidence of the preceding section, is the employment process. Being unemployed reduces the hazard of leaving poverty.

In the current model, the problem is minor, since this criticism could at most be applied to the old, living on social benefits. However, the density estimates reported in Schluter (1996) show that poverty is not a predominant old age phenomenon. Moreover, a poor old pensioner could alter her income state by entering the household of her children. The problem, however, is not completely absent given the previous results of the mover-stayer model.

¹⁴See Cox (1975) or Lancaster (1990) chapter 9 for a discussion of the partial likelihood function.

variables	ML estimates	standard errors
unemployment status	-.236	.0858
household size	.065	.029
nationality	-.1556	.091
age in 1984	-.0009	.0027

Table 3: The continuous-time Cox poverty hazard model

Furthermore, the plot of the baseline hazard rate $h(t)$ is derived by setting the parameter values β to zero. Inspecting the (not provided) plot of the non-parametric estimate of the baseline hazard rate, it increases at first, but then falls monotonically. Thus medium and long term poverty profiles differ with the latter exhibiting negative duration dependence. (Cf. also the non-parametric estimates of the discrete duration model.)¹⁵ Thus, the longer the poverty spell, the less likely is the person to escape from it. However, these findings must be considered tentative in the light of a result due to Heckman and Singer (1984). They have demonstrated that variable selection is a grave problem since "uncontrolled unobservables bias estimated hazard rates towards negative duration dependence". This follows since more mobile persons leave the less mobile persons behind, creating the appearance of stronger negative duration dependence than actually exists.

Unobservable heterogeneity can be modelled by introducing a mixing distribution, so that the hazard rate is perturbed by an unobservable random variable V . Following Lancaster (1979), let v be iid from a Gamma(1, η) distribution with variance η^{-1} , assumed to mimic the unobservables. Thus, the hazard rate for person i becomes

$$\lambda_i(t) = v_i \mu_i(t) \text{ where } \mu_i(t) = \alpha t^{\alpha-1} \exp(\beta' x_i(t)) \quad (6)$$

This specification leads to conditional distributions $F_i(t|v)$ and the unobservable v needs to be integrated out. This yields the unconditional distribution $F^*(t) = E_v(F_i(t|v)) = 1 - [1 + z(t)/\eta]^{-\eta}$ and density $f^*(t) = \mu(t)[1 + z(t)/\eta]^{-(1+\eta)}$ where $z(t) = \int_0^t \mu(s)ds$. The maximum likelihood estimation of the parameter vector (β, η) is carried out using the *EM*-algorithm (see the

¹⁵ $h(t)$ is often assumed to be Weibull, $h(t) = \alpha t^{\alpha-1}$, since a Weibull specification leads to a non-constant hazard rate (but nests within it the exponential distribution which exhibits a lack of memory). Duration dependence is negative (positive) if $\alpha < 1$ ($\alpha > 1$). Fitting a Weibull distribution leads to an estimate of $\hat{\alpha} = 0.833 < 1$, confirming the conjectured negative duration dependence.

appendix for a description). However, the resulting estimate of the variance of the mixing Gamma distribution, η^{-1} , is already very high on only the uncensored data, $\eta^{-1} = 14$. This implies that a Gamma mixing model, popular in the literature, is inappropriate in the present context.

It may be argued that the continuous time model is misspecified in that discrete-time data have inappropriately been treated as if they were continuous. Does a discrete-time model have different implications ?

The theory outlined above extends in a natural manner to the discrete-time case. For instance, the hazard rate now has the interpretation $\lambda_i(t) = \Pr\{T_i = t | T_i \geq t; x_i(t)\}$. As pointed out by Allison (1982) and reiterated by Jenkins (1996), estimation of this model is straightforward. Making the unit of analysis the spell month and thus reorganising the data, the likelihood function for the discrete-time duration model can be rewritten in a form which is standard in the analysis of a binary variable. Two parametrisations of the hazard rate are examined. First, the complementary log-log hazard rate $\lambda_i(t) = 1 - \exp\{-\exp\{h(t) + \beta'x_i(t)\}\}$ is chosen, since it is the counterpart of the underlying continuous time proportional hazard model examined above. But since there is no reason why hazard rates should be proportional, the second parametrisation is the logistic hazard rate $\lambda_i(t) = 1/(1 + \exp\{-h(t) - \beta'x_i(t)\})$.

The results of the estimation are reported in Table 4. The selected variables are the same as in the previous models. Duration dependence is captured by the baseline hazard $h(t)$, which is estimated non-parametrically by a sequence of dummies. The results of the two parametrisations are very similar. This should not be too surprising, since it is well known that the logistic model converges to the proportional hazard model as the hazard rate converges to zero. Once again, poverty spells of the long-term poor exhibit negative duration dependence. The hazard of leaving poverty is lower for foreign nationals, and the household formation process is neither important nor very significant. Finding employment is the principal way of escaping from poverty.

What are the determinants of re-entering poverty ? Applying a duration model to this issue is problematic, since sample sizes are small: there are 1050 single spells out of poverty which followed a poverty spell of which 70% are right censored. So the subsequent statistical analysis has to be regarded as tentative. However, this data structure suggests that for economically mobile persons (the movers in section 4) poverty is a predominantly transitory and rare event, which once overcome is unlikely to be experienced again.

The hazard rate $\lambda_i(t)$ now captures the probability of person i re-entering

model	c. log-log		logistic	
	ML estimates	SE	ML estimates	robust SE
duration=2 years	.138	.102	.169	.124
duration=3 years	-.163	.159	-.181	.185
duration=4 years	-.549	.232	-.64	.263
duration \geq 5 years	-.639	.504	-.73	.553
employment status	.407	.0818	.495	.099
household size	.0656	.0283	.0828	.034
nationality	-.161	.089	-.202	.105
disabled	-.044	.092	-.048	.108
education in 1984	.03	.021	.0377	.0268
age in 1984	.0014	.0027	.0018	.0032

Table 4: The discrete-time duration models of the hazard of leaving poverty

poverty at time t . The results of estimating the model with the two hazard parametrisations are reported in Table 5. The selected variables are those of the previous models. The estimates show the expected strong negative duration dependence: the longer the spell out of poverty, the less likely is the person to experience poverty again. The surprise, however, is that although the coefficients on all other explanatory variables have signs consistent with the previous results, they are not statistically significant. Moreover, the size of the employment coefficient is very small. This duration model is thus inadequate for analysing the probabilities of re-entering poverty.

How do these findings relate to results found by other researchers for other countries such as the US? The results are, in many ways, similar to those of Bane and Ellwood (1985). Using the PSID for the years 1970 to 1982, they find that most of those who become poor will have only a short stay in poverty, whilst the stock of the poor is predominantly composed of the long-term poor. The hazard of leaving poverty also exhibits negative duration dependence (although these are computed ignoring observable and unobservable population heterogeneity). Using cross-tabulation techniques, they find that earning changes explain 75% of all poverty spell endings, but this figure is dramatically lower for beginning spells. This result is mirrored in the German case by the importance of the (un)employment process. However, the household formation process is found to be of lesser importance than in the US. Since the current study analyses annual income data, the caveat of Ruggles and Williams (1989) applies, who, using monthly data, find that the typical poverty spell is much shorter than

model	c. log-log		logistic	
	ML estimates	SE	ML estimates	robust SE
duration=2 years	-.522	.139	-.676	.176
duration=3 years	-.88	.223	-1.1	.263
duration=4 years	-1.11	.279	-1.364	.317
duration \geq 5 years	-5.12	.326	-5.47	.33
employment status	-.039	.129	-.064	.166
household size	-.043	.045	-.059	.058
nationality	.07	.14	.0999	.185
disabled	.144	.135	.188	.177
education in 1984	-.005	.04	-.0076	.053
age in 1984	-.005	.04	-.004	.005

Table 5: The discrete-time duration models of the hazard of re-entering poverty

would be anticipated using annual data as 2/3 succeed in escaping poverty before 12 months.¹⁶

6 Conclusion

Intra-distributional mobility is a very important dimension of income dynamics and examining merely the shape dynamics of the income distribution is likely to result in misleading welfare judgments. In the German case, the lack of action at the surface conceals substantial movements beneath it. Indeed according to Friedman's criterion Germany has become a more unequal society because overall mobility has fallen.

Several statistical models based on transition matrices were estimated in order to provide a concise description of the mobility process. The transition probabilities vary with time and the process exhibits a memory which extends beyond one period. The mover-stayer models also suggest the importance of population heterogeneity.

In order to examine the economic determinants of the income process further and to go beyond the descriptive analysis, we have concentrated on one

¹⁶See also Blanc (1989) for a similar econometric approach in the context of AFDC spells in the US using monthly data. The principal focus of her analysis is duration dependence whose various parametrisations she compares with a non-parametric step-wise specification.

very important income state -poverty- instead of the entire transition matrix. Although different models were estimated - a Markov model with exogenous variables and several duration models - the principal findings are similar: unemployment is the principal determinant of poverty; in contrast to the US, the household formation process is only of minor importance, as are age and educational background. Poverty spells of the long-term poor exhibit negative duration dependence: the longer the poverty spell, the less likely is the person to escape poverty.

The current specifications of these models are very parsimonious and only one income state is examined. The economic determinants of income mobility warrent further research.

7 Appendix: The EM-Algorithm

This section describes the EM-algorithm used for maximum likelihood estimation in the poverty hazard model with unobservable heterogeneity. For a more detailed description see Cox and Oakes (1984) or Lancaster (1990), upon which the following discussion is based.

The EM-algorithm consists of two principal steps, viz. taking an Expectation, and Maximising the objective function thereafter.

Let the random variable V with realisation v be iid with distribution function $G(\cdot; \eta)$ and associated density $g(\cdot; \eta)$, known up to a parameter vector η . This process generates the unobservable heterogeneity. Let T with realisation t denote the random variable waiting time, parametrised such that its conditional density is $f(t|v; \beta, \eta) = v\mu(t; \beta) \exp(-vz(t; \beta))$ where $z(t; \beta) = \int_0^t \mu(s) ds$. The log-likelihood of the joint distribution of V and T is

$$\begin{aligned} \log L(\beta; \eta; t; v) &= \sum_{i=1}^N [\log f(t_i|v_i; \beta) + \log h(v_i|\eta)] \\ &= \sum_{i=1}^N [\log v_i + \log \mu(t_i; \beta) - v_i z(t_i; \beta) + \log g(v_i; \eta)] \end{aligned}$$

The algorithm proceeds as follows:

1. From an initial guess $(\beta_n; \eta_n)$ calculate the log-likelihood function of the joint distribution of V and T .
2. Calculate its expected value using the initial guess

$$Q((\beta; \eta) (\beta_n; \eta_n)) = E(\log L(\beta; \eta); V|t, (\beta_n; \eta_n))$$

In the context of the present model, the following calculations are typical. Since $g(v)$ and $f(t|v)$ are known, $f(v|t)$ can be calculated. The terms such as $E(V|t)$ and $E(\log V|t)$ are then readily derived.

3. Maximise this with respect to $(\beta; \eta)$. The solutions to the first order conditions define the new iteration values $(\beta_{n+1}; \eta_{n+1})$.

4. Continue to iterate until the value of the unconditional log-likelihood converges.

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